Incentives to Quality and Investment: Evidence from Electricity Distribution in Italy*

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Abstract – This paper focus on quality regulation and empirically investigates the effect of rewards and penalties schemes on the regulated firm's decision to use capital and non-capital resources to meet regulatory targets. To this end, we conduct an empirical analysis using micro data for the largest electricity distribution operator in Italy (86% of the market), where output-based incentives have been applied to indicators of service quality for over a decade. Using a dataset collected with the support of the Italian energy regulatory authority for the period 2004-2009, we first show that service quality is indeed affected by capital and non-capital expenditures. Then, by investigating the causality link between firm's expenditures and regulatory incentives, we provide evidence that output-based incentives affect capital expenditures, but not vice versa. Lastly, we adopt a more comprehensive approach to investigate the relationship between quality-related incentives and expenditure decisions. Our results reveal an asymmetric effect of rewards and penalties on capital expenditures' decisions across areas with different quality levels. From these findings, we derive several policy implications.

Keywords – Electricity distribution, Incentive regulation, Investment, Service quality

JEL Classification: L51, L94

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1. Introduction

Since the introduction of structural reforms in network industries, incentive regulation of energy networks has focused on the use of firm inputs (operational and capital expenditures), which have the purpose of stimulating productive efficiency and new investments. Only few directly measurable outputs have been historically associated with the explicit definition of performance targets and coupled with specific financial incentives. In most cases, these output-based incentives were used to reduce network losses and/or to improve service quality (Jamasb and Pollit, 2007; Joskow, 2008). As for Italy, the energy regulatory authority (*Autorità per l'energia elettrica, il gas e il servizio idrico,* AEEGSI) has been applying output-based regulation to indicators of service quality since 2000.

In the past few years, national energy regulatory authorities started focusing on additional goals, such as sustainability and innovation. These new areas as well are (or are expected to be) regulated with output-based incentives, that reward/penalize companies on the basis of their performance with respect to measures of the firms' ability to reduce their environmental impact, to enable the integration new technologies (dispersed generation or electrical vehicles), and so on. The *Revenue, Innovation, Incentives and Output* (RIIO) model, recently adopted by the energy regulatory authority in the UK (Ofgem, 2010), is probably the best-known example in this regard, but other European regulatory agencies are moving in this direction as well.[1] Also in the US, ad-hoc regulatory incentives are currently adopted, in virtually all states, for specific output-based targets, that include energy efficiency and environmental sustainability.[2]

This paper empirically investigates the relationship between output-based incentives for service quality and the use capital and non-capital resources to meet regulatory targets by the largest electricity distribution operator (86% of total distributed energy) in Italy. The primary aim of the paper is to understand whether rewards and penalties are both needed to spur such expenditures and, in turn, service quality, or if rewards (and penalties) simply push (and subtract) money towards companies for their past superior (inferior) performance, without affecting firms' decisions. Our analysis can thus provide insights to national regulators on how to calibrate incentive payments and prevent unnecessary transfers from consumers to the regulated firm (and vice versa). Output-based regulatory mechanisms are indeed

[1] As for Italy, see Lo Schiavo et al. (2013).
[2] For an overview of the regulatory regimes in the US electric utility industry on alternative output based goals in the US, see IEE (2013).

complex to implement and require significant regulatory resources (powers, budget and skills), for data collection and monitoring, as well as periodical adjustments over time (Joskow, 2008; Jamasb et al. 2012). From a policy perspective, our analysis is therefore relevant in view of the direct regulatory costs of current and future regulatory frameworks.

Among EU national regulators, the Italian energy regulatory Authority (AEEGSI) has been a frontrunner in the introduction of specific quality-based incentive schemes in electric distribution. To test the effect of output based incentives, we use micro data on electricity distribution, collected with the support of the AEEGSI, through a dedicated survey on the activity of the largest distributor in Italy, *Enel Distribuzione*, which operates throughout the national territory. The company is part of *ENEL* group, the former electricity state monopolist, privatized in 1999 and publicly listed. Although the company is formally state-controlled, currently almost 75% is publicly traded (67% in 2009), so its behavior, including the responsiveness to regulatory and incentive policies is similar to that of privately-controlled quoted firms.[3] The dataset is a comprehensive and balanced panel of *Enel*'s 115 distribution Zones (or units), which includes unit-level accounting data from 2004 to 2009 and, more importantly for us, the amounts annually received in rewards (paid in penalties) for service quality – data that are generally available only to national regulatory agencies. This information on incentive (rewards and penalties) payments is a key feature of this paper in that, differently from previous studies, it allows us to investigate if incentive payments affect the capital and non-capital expenditure decisions and whether this effect is asymmetric between rewards and penalties and differs among areas with different quality levels.

Another distinctive feature in the case of *Enel Distribuzione* is in the detail of the technical microdata, which allow us to measure the technical changes and the innovations adopted by the company following the introduction of quality regulation in Italy (see, Cerretti et al., 2005 and Valtorta et al., 2009). In fact, a well known problem with distribution networks is that, while some quality-specific investments can be identified and isolated, many if not most technical and structural interventions are "multiple purposes" and respond to quality-related goals among the others. The fact that the company's response to quality-specific incentives is (at least partially) measurable is a step forward with respect to the existing literature. In particular, the regulator has collected unit-level microdata on the type, location and timing of several technical interventions carried out by *Enel Distribuzione*

[3] Note that the ownership share held by the state through municipalities in the other Italian distributors is always larger than 50%, for example, A2A – Milan with 54%, ACEA - Rome with 51%, AEM (now IREN) – Genoa and Turin with 54%.

over the territory it serves. Such detailed micro-level information is not available for any other jurisdiction served by alternative distributors in Italy and, to our knowledge, has never been exploited for similar analyses in other countries.

The economic literature provides some evidence on the relationship between input-based incentive regulation (e.g. price/revenue caps), quality-specific incentives and the level of service quality. In a comprehensive survey, Sappington (2005) highlights how the introduction of minimum quality standards and/or rewards and penalties schemes is necessary to secure a desirable level of service quality in presence of high-powered incentive mechanisms. Empirical evidence supports these insights, by showing that the introduction of quality standards (in general, not necessarily output-based regulation) is relevant in ensuring that firms achieve cost savings without an adverse effect on quality (Reichl et al., 2008; Ter-Martisoryan and Kwoka, 2010).

Differently from previous work (Ter-Martisoryan and Kwoka, 2010) that looked into the effect of the presence of quality regulation in the form of a dichotomous variable, we employ here the annual monetary amounts actually assigned to (paid by) each distribution unit as a result of its quality performance, within an output-based mechanism. We start with the assumption that output-based incentives are expected to influence performance (with respect to the regulated output) by inducing firms to invest in capital assets and/or additional operating expenses – ideally maintenance costs – in order to meet the regulatory target (Jamasb et al., 2012). In theory (Sappington, 2005; De Fraja and Iozzi, 2008), firm's decision to exert an effort is conditional on (marginal) incentives being larger (in absolute value) than firm's (marginal) costs of (providing) quality. Given that incentives reflect consumer willingness to pay for quality, this mechanism induces regulated firms to deliver welfare-maximizing levels of performance. In this paper, we test the interplay between quality-related incentives and firm investment.

Previous empirical work has related the level of regulatory incentives (per unit of quality improvement) with the estimated per unit cost of quality improvement (Jamasb et al., 2012; Coelli et al., 2013). Finding that actual unitary incentives are higher (lower) than estimated per unit costs, the authors infer that firms are likely (not likely) to improve service quality. In other words, they assume that the prospect of gaining a reward (paying a penalty) would induce firms to spend on quality, provided incentives are higher than costs.

We differ from this approach in that we analyze the actual strategy of a large distribution firm that is subject to output regulation and aims at obtaining higher service quality as a consequence. Specifically, we investigate whether incentives to quality affect the firm's decision to invest in capital and operational expenditures in order to improve quality (a mechanism that may recall industrial policy interventions that offer tax incentives for R&D and innovation in manufacturing firms). Incentives are assigned at the end of the year, based on the observed performance. Therefore, it may happen that not only *expected* rewards/penalties incentives (as in Jamasb et al., 2012), but also rewards or penalties *received* or *paid* at the end of the year positively affect future investments, in that they generate cash in-flows or out-flows that ultimately influence expenditure decisions.

Given the empirical setting of the Italian system, in the econometric analysis we account for this articulated timing of the incentive procedure and carry out the analysis by proceeding along three steps.

First, we provide evidence that quality (measured by the average duration of service interruptions, i.e. the indicator of service quality that has been subject to regulatory control in Italy for the longest time) is affected by operational expenses (which aggregate maintenance as well as operational costs) and by investments in physical assets. This result is in line with empirical evidence by Ter-Martirosyan and Kwoka (2010) for the U.S., which shows that the same quality indicator is affected by maintenance expenditures. This step serves the specific purpose to verify that, by increasing the available fixed assets and equipment and/or the aggregate operational expenditures, firms succeed in improving their quality performance.

Second, we analyze the relationship between capital and operational expenditures and regulatory incentives. By employing the Granger (1969) and Sims (1972) causality test, we show that past incentives positively affect current capital expenditures, which suggests a causal relationship from output-based incentives to firm investment. In contrast, we find no evidence of a causal relationship between incentives to quality and operational expenses.

Finally, we test whether the impact of output-based incentives on the investment rate survives after controlling for other determinants. To this end, we estimate a dynamic accelerator model of investment with financial effects that includes lagged regulatory incentives among the explanatory variables. Furthermore, in order to investigate the potential asymmetries between positive and negative incentives, we decouple rewards and penalties within the investment analysis. Our findings show that penalties (paid) play a significant role in the decision to invest, especially so if the quality performance is very low, i.e. for areas with a quality in the fourth quartile of distribution. Rewards (received) appear, instead, to affect the investment decision only in areas with top quality performance (first quartile), but not in the remaining areas. Interestingly, moreover, neither rewards nor penalties appear to affect the investment decision in distribution units with an average quality performance. Our results actually throw some light on the role of positive monetary incentives. A premium rewards the unit for having achieved a desirable level of performance – hence quality incentives are not assigned in vain -, but one should not necessarily expect that the same rewards unambiguously prompt the unit to further improve on it. Only in highly performing areas do rewards matter, probably due to favorable external conditions that influence the ability of the distribution unit to exceed the targets imposed by quality regulation.

The rest of this paper is organized as follows. Section 2 provides the relevant details of the Italian regulatory framework. Section 3 describes the research design and the empirical methodology. Section 4 illustrates the dataset and the variables used in the estimations. Section 5 presents the estimates from the regression analyses and discusses the results. Section 6 concludes and derives policy implications.

2. Regulatory incentives in the Italian electricity distribution sector

The structure of the Italian electricity distribution sector has been quite stable for the past ten years. At the end of 2013, it counted 136 Distribution System Operators (DSO) that delivered a total volume of 269 TWh. In 2009, the last year observed in this analysis, the number of DSOs was 140 and the delivered volumes amounted to 280 TWh. The largest firm and historical incumbent operator, *Enel Distribuzione,* was responsible for 86.2% of the distributed energy, followed by *A2A Reti Elettriche* (4.1%), *Acea Distribuzione* (3.6%) and *Aem Torino Distribuzione* (1.3%), serving the urban areas of Milan, Rome and Turin, respectively. None of the other operators delivered more than 1% of total distributed energy. This is true also today.

Since 2000, the regulatory framework includes both input-based and output-based incentives: the former have the main objective to stimulate productive efficiency, the latter to ensure an adequate level of service quality. As for productive efficiency, a price cap mechanism applies to operational expenditures, which are required to annually decrease with an *X* efficiency factor. Differently, depreciation and the cost of capital are directly passed through to consumers. The cost of capital is remunerated with a fixed rate of return, estimated with a Weighted Average Cost of Capital (WACC) methodology.[4]

[4] For the second tariff period (2004-2007) WACC was set 6.8% and the *X* factor at 3.5%. For the third tariff period (2008-2011) the WACC was increased to 7% and the *X* factor was decreased to 1.9%. For the current, fourth tariff period (2012-2015) the WACC is set at 8.6% for the first two years and at 6.4% for the remaining two years; the *X* factor is set at 2.8%. Details on the choice of the WACC and *X* factors in the energy sector in

Service quality regulation encompasses several dimensions, ranging from commercial quality aspects (e.g., appointment scheduling) to highly specific technical characteristics (e.g., voltage dips). Different quality dimensions are controlled using different approaches (Fumagalli et al., 2007). Output-based incentives are specifically employed in Italy to regulate continuity of supply, i.e., the occurrence of service interruptions, with two main objectives: *(i)* to improve continuity levels and *(ii)* to reduce the differences in continuity levels observed across different geographical regions.

To this end, AEEGSI requires DSOs to measure, on an annual basis, the average number and duration of service interruptions per customer. For a given distribution unit and year, the average duration of long interruptions (longer than 3 minutes) per consumer is indicated with the acronym SAIDI (System Average Interruption Duration Index) and calculated as:

$$SAIDI = \sum_{k=1}^{M} \frac{D_k N_k}{N_{tot}}$$

where the sum extends over all M interruptions in a year ($k = 1,\ldots M$), D_k is the duration of interruption k (in minutes), N_k is the number of consumers affected by interruption k, and N_{tot} is the total number of consumers served in the distribution unit.[5]

This indicator is measured, separately, in more than 300 *territorial districts* that cover the entire national territory. Each district includes municipalities that are homogeneous in population density, that are located in the same administrative province and whose network is managed by the same distribution company.[6] For each district, AEEGSI defines an annual target (more on this below) and requires companies to report, each year, the difference

Europe can be found in Cambini and Rondi (2010). Specific investment benefits have been introduced to support, for instance, the deployment of low-loss transformers and to promote automation and control of active grids (Lo Schiavo et al., 2013)

[5] In addition to SAIDI the Italian regulation requires distribution companies to report the average number of long interruptions per customer, known by the acronym SAIFI (System Average Interruption Frequency Index), as well as the average number of short (shorter than 3 minutes and longer than 1 second) interruptions per customer: this index is called MAIFI (Momentary Average Interruption Frequency Index). The average number of long (short) interruptions per consumer is calculated as:

$$SAIFI\ (MAIFI) = \sum_{k=1}^{M} \frac{N_k}{N_{tot}}$$

where notation is as above. From 2000 to 2007 rewards and penalties were applied to SAIDI only. From 2008 onwards, rewards and penalties apply to SAIDI as well as to another indicator calculated as the sum of SAIFI plus MAIFI (total number of interruptions, long and short ones).

[6] Each of the Enel's units (Zones) includes two or three districts, typically of different density levels (see also Section 4).

between the actual indicator and the target. Economic incentives ($INC_{j,t}$) per district j and year t are calculated, as follows:

$$INC_{j,t} = DeltaSAIDI_{j,t} \cdot (C_1 \frac{res\_energy_{j,t}}{8.76} + C_2 \frac{nonres\_energy_{j,t}}{8.76}) \quad (1)$$

where:

- $DeltaSAIDI_{j,t}$ (in minutes) is the difference between the target SAIDI and the actual SAIDI for district j in year t; actual and target SAIDI do not include notified interruptions nor events that are not under the responsibility of the distributor (more on this below);
- C_1 and C_2 are unitary incentives set by AEEGSI at, respectively, 18 c€/(minute·kW) and 36 c€/(minute·kW): they reflect the different willingness to pay for quality of, respectively, residential and non-residential customers, as estimated by means of a customer survey (AEEGSI, 2007);
- $res\_energy_{j,t}$ and $nonres\_energy_{j,t}$ are, respectively, residential and non-residential energy consumption per district j and year t (in MWh).

Several remarks are in order. First, AEEGSI sets targets using a formula that implies a convergence in performance of all districts with equal population density to the same quality level, the so called *national standard*, in the medium term (12 years from 2004 for SAIDI). This implies that targets are more demanding every year, until district performance reaches the set national standard, and also that greater quality improvements are required in districts which reported lower levels of performance when the medium-term target was set. The intrinsic motivation for this choice is that the Italian legislation requires distribution tariffs to be the same across the entire national territory: the same quality should be associated to the same level of customer expenditure. This also implies that annual rewards received (or penalties paid) for each district are withdrawn (injected) into a single account. At the end of the year, if the account has a surplus, this is equally distributed to consumers by a decrease in the distribution tariff. Vice versa, if the account has a deficit the distribution tariff is increased. In this manner costs (savings) for higher (lower) levels of quality are socialized among consumers, while quality-related incentives remain district-specific for the regulated companies.[7]

Second, the national standard of performance is differentiated per population density so that more densely populated districts are expected to provide higher levels of continuity, i.e. a higher quality. In other words, regulation accounts for technical differences in urban, suburban and rural distribution districts.[8]

Finally, we observe that registered interruption events are classified per cause and origin of the fault (e.g., transmission network, Force Majeure, etc.). Although our data set includes, separately, the average duration and number of (long and short) interruptions for all events, in this paper we consider only events that, according to the regulatory definition, fall under the responsibility of the distributor.[9] All other interruptions do not contribute to the regulated part of the total SAIDI and do not enter in the calculation of rewards and penalties. For this reason, they are excluded also from our empirical analysis.

3. Research design

The focus of this paper is on the effectiveness of output-based incentive schemes. Specifically, we explore whether these incentives affect the use of those resources that are most likely to affect performance with respect to the regulated outputs.

Differently from previous work (Jamasb et al., 2012; Coelli et al., 2013), we empirically study the relationship between annual monetary incentives and the observed level of expenditures. To this end, several issues need to be considered.

First, there is an ambiguity issue, since the observation of an increase in expenses can be associated both with an increase and with a decrease in quality (Jamasb et al., 2012). On the one hand, the longer and more frequent are the interruptions, the higher will be the expenses incurred to repair the faults, including personnel related costs (we refer to these as corrective costs). On the other hand, expenses (i.e. preventive costs) will increase whenever the firm

[7] In the time span of our analysis, the average household has paid an extra cost due to quality increments of about 2 €/year. The cost of continuity regulation was accounted for in the distribution charges of the electricity bill. For the average household the latter amounts to around 500 €/year.

[8] Urban networks present, compared to rural networks, shorter feeders, a higher share of underground cables and a higher level of redundancy. These structural characteristics favor continuity of supply.

[9] In particular, the Italian regulation makes a distinction between interruption events and exceptional interruption events or, better, “exceptional time periods”. Since 2004 these events (time periods) are identified using a statistical methodology which, originally, identified an extreme region in the daily SAIDI (and SAIFI) plane, where such exceptional events (periods) belonged to. The boundaries of this region were originally defined for each district using thresholds of means and standard deviations of daily SAIDIs (for details see Fumagalli et al., 2009). Such exceptional events (thus including extreme weather) are considered as caused by Force Majeure.

implements specific actions (e.g. more frequent maintenance interventions, structural changes in the network, etc.), to improve service-quality. The nature of the relationship between performance, incentives and expenditures is laid out in Figure 1. As shown in the diagram, we expect that physical equipment in year *t* defines the level of quality in the same year, while the effect of new investments in year *t* will be evident in subsequent years (are expected to ameliorate future quality). The same holds for maintenance expenditures (effects are to be seen in the future). Differently, expenditures in operations in year *t* can be influenced by the level of quality in the same year and can also influence the level of quality in the same year. Figure 1 also shows that quality levels, calculated at the end of each year, determine rewards/penalties for the same year; as such, monetary incentives can enter the decision making for expenditures made in the subsequent year.

This implies that there is also a causality issue. As we set out to explore whether incentives influence investment or operational expenditures and, in turn, quality, we need to consider that quality does determine the rewards or the penalties, i.e. the incentives granted to the firm by the regulator. Hence, the need to test the direction of causality between the incentive scheme and the investment or maintenance plans.

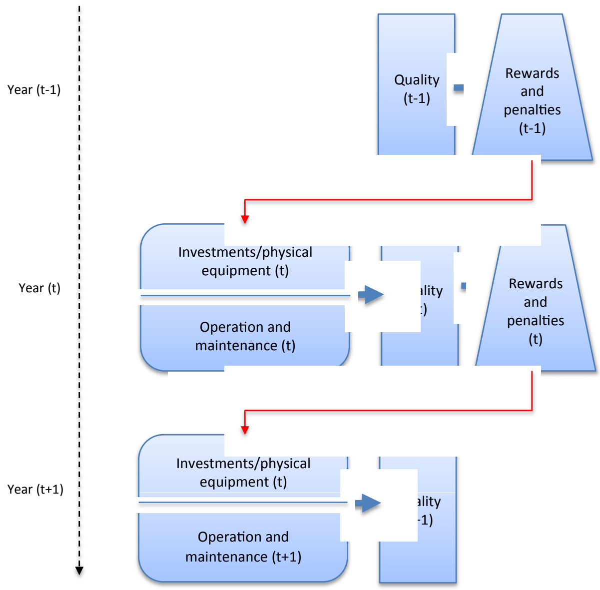

Figure 1 – Incentives, expenditures and quality

The third issue deals with the organization of distribution, as companies, including *Enel*, often manage electricity distribution units that are geographically separated. Therefore, in general, with firm-level data, it is not easy to match the performance of a single distribution unit with the operator’s attempt to improve service quality in that same geographical area.

The peculiar nature of the micro data in our database allows us to deal with this problem in a very detailed and comprehensive manner in that we can rely on both accounting data and physical characteristics of the capital endowment for each distribution unit (Zone) within the company (see Section 4 for an extensive description of the dataset). Moreover, we can match these unit-level data with quality output achieved in each (narrowly defined) area. In addition, a key feature of these distribution units is that they account for individual and separate managerial decision units within the company, so it is not inappropriate to view them as firms or quasi-firms.

Finally, when applied to distribution operators, the usual measurement problems that arise in calculating the investment rate (i.e. the ratio of gross fixed investment to capital stock at replacement value) for standard manufacturing firms become more complicated. On the one hand, ideally we need sensitive accounting data at the level of distribution units (see above). On the other hand, the available accounting monetary values of capital expenditures and fixed capital stock used to calculate the investment rate are usually excessively aggregated. In our exercise, these accounting monetary values have to be related to a particular kind of output, i.e. customer minutes lost. Our micro data also help us cope with this problem in that they comprise technical data on several physical components of the distribution network (for instance, the number of automated secondary substations), whose presence can be directly related to higher continuity levels, hence to higher quality.

To deal with the first and second issues, i.e. ambiguity and causality of the impact of expenses, our research strategy proceeds in three steps.

In the first step, we investigate the relationship between the continuity of supply (SAIDI) and firms' capital and non-capital resources. One novelty of our approach is that we proxy for capital expenditures with a number of *physical* characteristics of the distribution network (e.g. the number of automated secondary substations) that is generally considered as specifically influencing the number of power interruptions and lost minutes. An additional advantage of this strategy is that it enables us to connect supply continuity with the actual physical assets employed in the *distribution area*.

In the second step, we explore the issue of causality between output-based regulatory incentives and the use of firm resources that are supposed to affect the level of quality (i.e. the determinants of continuity of supply analyzed in the first step). To this purpose, we consider capital expenditures and operational expenditures, both expressed in monetary values since we now relate them to monetary incentives. To establish the direction of causality between capital or operational expenditures and regulatory output-based incentives, we apply the Granger (1969) and Sims (1972) *weak-causality* test, which tests whether an increase in incentives is followed by an increase in capital (or operational) expenditures or vice versa.[10] The test allows for three alternative possibilities. First, it may be that past incentives prompt the unit's manager to upgrade the network (i.e. the service), in which case we can say that incentives Granger-cause capital (or non-capital) expenditures. Alternatively, it could be that, following past increases (or decreases) in capital or operational spending, the unit/firm will be granted a reward (or a penalty). In this case, we can say that it is firm's expenditures which Granger-cause incentives. Finally, we may find evidence of circularity, i.e. a two-way causality whereby an increase in (capital or operational) expenditures is followed by an increase in incentives, and vice-versa.

The third step builds on the results of the Granger causality test. Considering that the specification of the Granger model is relatively simple, in that it just focuses on the dynamic relationship between investment and incentives, it can be argued that the relationship is driven by other unobserved variables. For example, incentives are definitely either a cash-flow entry (rewards) or a cash-flow exit (penalties) and investments are notoriously related with cash-flow. To better account for the complexity of the investment decision, we adopt a more comprehensive approach and estimate an accelerator investment model that controls for financial factors (Bond et al., 2003) to investigate the impact of quality-related incentives on investments. The objective of this analysis is twofold. First, we test whether the dynamic effect of incentives on investment survives when we control for other determinants. Second, we test whether penalties and rewards present similar or asymmetric effects on the investment rate.

4. The sample and the data

We built the dataset with the support of the Italian energy regulatory authority, by means of a dedicated data collection. It is a comprehensive and balanced panel for 115 distribution units (called Zones) that belong to *Enel Distribuzione*, tracked from 2004 to 2009. Given *Enel*'s market share (86% in 2009) and its presence over the entire national territory, our data provides a good representation of the Italian electricity distribution sector.

[10] See Arellano (2003, Ch. 6) for details regarding the use of Granger causality tests in the context of a panel setting. Granger causality tests were recently used to examine several regulatory issues such as tariff rates, leverage, investment, intensity of regulation, regulatory independence, etc. (Edwards and Waverman, 2006; Bortolotti et al., 2011; Cambini and Rondi, 2012).

The dataset includes unique technical and accounting micro data for each of the *Enel*'s 115 units. Continuity indicator (SAIDI) as well as the amounts annually received in rewards (paid in penalties) are available, instead, per *district*, which are geographical areas smaller than *Enel*'s managerial *units*, so that each Zone includes two to three (clearly identifiable) districts, typically of different density levels. To ensure coherence with technical and accounting data, we used the number of low voltage consumers in each district as weights to compute for each Zone the continuity indicator as well as quality-related incentives.[11] Several details regarding duration and frequency of interruptions, as well as the amounts of rewards received and penalties paid per district are not publicly available data and were directly provided by the regulator.

4.1. Data and summary statistics

By effect of the current regulatory setting (described in Section 2), our sample is composed of units of observation that are subject to (input-based) incentives to reduce operational costs, but also relatively free to choose the desired level of investment. At the same time, rewards (penalties) associated with quality performance, can increase (decrease) the amount of revenues collected by the distribution unit which meets (fails to meet) the regulatory targets in terms of quality.

In the observed time span, both price and quality regulation evolved across two regulatory periods (2004-2007 and 2008-2009). Apart from a few, expected adjustments, the general regulatory framework remained the same within the entire period of observation.[12]

By looking at service continuity data from 2004 to 2009, we observe a decreasing rate of improvement in performance over time. As illustrated in Figure 2 (on the right), the average duration of long (longer than 3 min.) interruptions per consumer (actual SAIDI) registered the largest improvements in the years 2005 and 2006; after that, only smaller changes in quality are visible. A similar trend (Figure 2, on the left) can be observed for the average number of long interruptions per consumer (actual SAIFI). While from a technological perspective such a trend is to be expected, it also provides an interesting environment for exploring the effectiveness of the output-based incentive scheme.

[11] By combining district-wide data into Zone-wide data, the relation between population density and continuity of supply (duration and frequency of interruptions, but also penalties and rewards) becomes considerably less precise.
[12] Even so, in our empirical analysis we do test for differences across the two periods. We thank an anonymous referee for this suggestion.

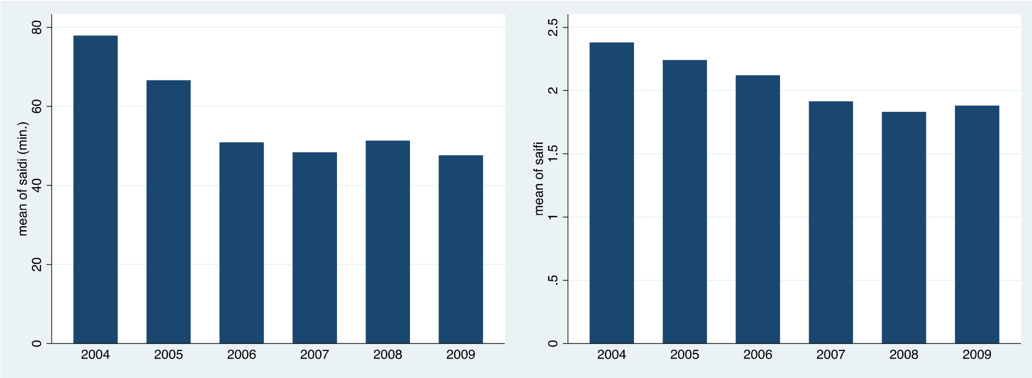

Figure 2 – Actual SAIDI (right) and SAIFI (left) over the observed period

Our measure of quality performance is the average duration of long interruptions per consumer (variable *SAIDI*).[13] The choice of this variable is motivated by the fact that SAIDI is included in the regulatory incentive scheme for the entire observation period, whereas monetary incentives for SAIFI were introduced only in 2008. Accordingly, to measure output-based incentives we use a variable which is equal to the amount received in rewards or paid in penalties for meeting (failing to meet) SAIDI-related targets (*INC*) – adjusted for inflation by using the Consumer Price Index at 2005 and excluding SAIFI-related incentives. This variable can assume positive and negative values, depending on the year. Hence, for the purpose of this work we also employ a variable (*REWARD*) which is equal to the variable *INC* if this is positive (and zero otherwise), as well as a variable (*PENALTY*) which is equal to the variable *INC* if this is negative (and zero otherwise). Note that, over the observed period, the occurrence of positive values (rewards) has always outnumbered the occurrence of negative values (penalties).

To investigate potential determinants of the variable *SAIDI*, we use capital and non-capital resources, i.e. fixed capital assets and operational expenditures, as well as control variables to account for specific characteristics of the distribution unit.

The set of physical asset components include the share of underground cable over total network length (*UNDER*), the number of automated secondary substations per Low Voltage (LV) consumer (*AUTO_LVcons*) and the number of Petersen coils, also per LV consumer (*PC_LVcons*). The variable *UNDER* is commonly used in the literature to capture the type of the distribution territory (grounding of MV feeders is a standard choice in areas with higher population density) as well as the additional burden in terms of capital assets (Kuosmanen,

[13] As already mentioned, the variable *SAIDI* coincides with the regulated part of total SAIDI (e.g., it does not include notified interruptions, nor events that originated on the transmission network or that were caused by Force Majeure). Also, it was winsorized to exclude an outlier in the first year of observation.

2012). This variable is also closely related to continuity of supply: underground cables are normally associated with a lower probability of fault. The number of automated secondary substations and of Petersen coils describe the infrastructural investments made by *Enel Distribuzione* as a response to continuity of supply regulation (Cerretti et al., 2005; Valtorta et al., 2009). The former has a role in decreasing the fault selection time and the latter in reducing the number of interruptions.

Non-capital resources, i.e. operational expenditures, are defined as the sum of costs incurred for labor, services, materials and other costs (*OPEX*) – adjusted for inflation by using the Consumer Price Index at 2005. Specifically, the explanatory variable employed here (*OPEX_LVcons*) is constructed as the ratio of *OPEX* to the number of LV consumers.[14]

As a control for specific characteristics of the distribution unit we employ the percentage of non-residential consumption (*PERC_NR*), obtained as the ratio of LV non-residential consumption plus medium voltage consumption over total consumption. It accounts for a higher willingness to pay for quality and for higher revenues per customer. It is typically associated with better continuity of supply.[15] Moreover, as shown by Jamasb et al. (2012), also weather conditions may affect service quality. We thus add two weather variables sourced from the Italian National Statistic Institute (ISTAT): the yearly average amount of precipitation (*PRECIPITATION*)[16] and the yearly average minimum temperature (*MIN TEMP*).

To estimate Granger tests and investment equations the key variables are the investment rate, the unit-level control variables, and the regulatory incentives. For the investment rate, we start from the accounting values of gross fixed investment (capital expenditures) and fixed capital stock at replacement value to calculate the investment (*I*) to beginning of year capital stock (*K*) ratio (IK_t).[17] Additional control variables that we include in the empirical

[14] Non-capital resources are represented in Ter-Martirosyan and Kwoka (2010) by two variables, operations expenses (that cover current firm operations) and maintenance expenses (that involve servicing the infrastructure). Our dataset does not allow us to distinguish between the two and we are bound to employ a single variable which, inevitably, aggregates preventive as well as corrective costs.

[15] Ter-Martirosyan and Kwoka (2010) employ average income per capita or per capita consumption with the same purpose. Other potentially interesting control variables, such as zonal density or the average length of feeders per substation report a high correlation with the variable *UNDER* (respectively, 0.666 and -0.575). Hence, they were not included in the analysis.

[16] The publicly available data from ISTAT are provided per administrative province, which closely matches *Enel*'s distribution units. Precipitation is defined as rain, snow, sleet or hail that falls on the ground and is measured in mm.

[17] Accounting data typically include only historic cost valuations of fixed assets (capital stock), which usually bear little relation to current replacement cost of long-lived fixed capital assets. Hence, we calculate the replacement cost of the capital stock using the perpetual inventory formula: $p_{t+1}K_{t+1} = p_tK_t(1-\delta)(p_{t+1}/p_t) + p_{t+1}I_{t+1}$, where p_t is the domestic price index of investment goods in period t sourced by the ISTAT (the National Institute of Statistics), K_t is the fixed capital stock in period t, I_t is the investment flow in period t, and δ is the

investment model are the operating cash flow (including depreciations, *Π*) to the beginning of year capital stock ratio ($ΠK_t$) and the revenues from sales (*S*) to the beginning of year capital stock ratio (SK_t). Regulatory incentives enter the investment model as ratios over the beginning of year capital stock (respectively, $INCK_t$, $REWARDK_t$, $PENALTYK_t$), in the same way as operational expenditures enter the Granger test as ratios over the beginning of year capital stock (OpK_t).[18]

Finally, several variables are employed as external instruments: zonal density, measured by the number of LV consumers over network length (*DENSITY*), the area covered by forests (*FOREST*) and two dummy variables, one (*NORTH*) accounting for Zones located in the North of Italy (the more industrialized part of the country) and one (*COAST*) capturing the proximity to the sea.

Table 1 summarizes the variables' descriptions. Table 2 reports basic descriptive statistics and Table 3 reports average economic performance of distribution units in terms of investments, operational expenditures and incentives by SAIDI quartiles. The most relevant features of the distribution across SAIDI quartiles are not only the obvious negative relationship between continuity of supply and incentives, but, more interestingly for us, the negative relation between SAIDI, the investment rate and the operational expenses. Table 3 also highlights that the amount of incentives is not trivial with respect to investment and operational expenditures. Rewards represent 22.8% of investment outlays at the top quartile (best performers) and only 9.5% at the bottom quartile. Penalties are in practice nonexistent among top performers, and mount to almost 2% of the investment outlays for units with the lowest quality performance. Finally, with respect to operational expenditures, on average, incentives account for 10.1% of operational expenditures in the top quartile and for 2.2% in the bottom quartile.

5. Empirical strategy and estimation results

5.1 Determinants of continuity of supply (step one)

To study the determinants of continuity of supply, we estimate a fixed-effects model, where *SAIDI* (in minutes) is the dependent variable. Explanatory variables include capital and non-capital resources, as well as control variables, as described in Section 4 (see also Table 2).

depreciation rate. The sector specific depreciation rate for the energy sector (4.4%) is derived from Bureau of Economic Analysis estimates reported in "Rates of Depreciation, Service Lives, Declining Balance Rates, and Hulten-Wykoff Categories".

[18] When taken as ratios to the beginning of year capital stock, variables *INC*, *REWARD*, *PENALTY* and *OPEX* are not adjusted for inflation.

To proxy for capital resources, we fully exploit our micro dataset and consider only equipment whose main purpose is to lower the duration and frequency of *regulated* interruptions (that are included in the calculation of rewards and penalties). While our dataset includes detailed physical measures of such equipment, it does not provide separate monetary amounts spent on these assets alone. A well-known technical and accounting problem with distribution networks is that while some quality-specific assets can be clearly identified, other structural interventions made by the distributor have multiple purposes and respond to quality-related goals as well as to other goals. The fact that we have, at least, the physical measure of these (clearly identifiable) quality-specific interventions is useful in this first step, which investigates the determinants of a physical measure of the quality of distribution (in minutes). However, we deemed it sensible to consider a comprehensive investment rate in step two and three and account for a larger possible set of interventions that can improve the level of quality. For these reasons, when the focus of the analysis shifts to the *monetary* value of the economic incentives, we switch to using the monetary value of fixed capital assets (from Section 5.2 onwards). Instead, for non-capital resources, the nature of the data prevent us from including only quality-specific measures of operational expenses and we have to rely on aggregated accounting values.

The model takes the following form:

$$SAIDI_{i,t} = \alpha_0 + \alpha_1 UNDER_{i,t} + \alpha_2 AUTO\_LVcons_{i,t} + \alpha_3 PC\_LVcons_{i,t} + \\ + \alpha_4 OPEX\_LVcons_{i,t} + \alpha_5 PERC\_NR_{i,t} \\ + \alpha_6 PRECIPITATION_{i,t} + \alpha_7 MIN\_TEMP_{i,t} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where *i* indicates the distribution unit (Zone) and *t* the year. The model includes unit (i.e. Zone), μ_i, and year, λ_t, dummies, and an error term, ε_{it}. As usual, firm fixed effects account for all time invariant observable and unobservable variables.[19]

Column (1) in Table 4 presents the results of a simple specification where we include only the physical asset components as well as additional unit-specific controls. Column (2) illustrates the results of a model with operational expenditures only, while Column (3)

[19] Given the presence of a number of potentially relevant time invariant territorial characteristics, we started the empirical analysis by estimating a random effects panel model. However, although the random effects estimates are more efficient than fixed effects estimates, in order to be valid, one must ensure that the individual invariant component in the error term is not correlated with regressors. To test for the consistency of the random effects coefficients we thus employed the Hausman (1978) specification test, but in all specifications the results pointed us to use fixed effects estimation.

presents the full model, including both operational expenditures and physical asset components. Altogether we are able to establish that selected capital resources have a significant effect on the level of service quality. In particular, this is true for the share of underground lines (*UNDER*) and for the number of automated secondary substations (*AUTO_LVcons*) – both exhibit the expected sign. The number of Petersen coils (*PC_LVcons*) shows the expected sign, but does not appear to have a significant effect on the dependent variable. This might depend on the fact that Petersen coils are installed to reduce the number of interruptions: their effect on the duration of interruptions is only indirect. Differently, operational expenditures (*OPEX_LVcons*) show a significant and positive effect on *SAIDI*. We interpret this as a prevalence (in our aggregate variable) of corrective costs, i.e. operational costs associated with the need to respond to network failures. Finally, we observe an unexpected positive sign on the share of non-residential energy consumption (*PERC_NR*) and on the minimum temperature variable (*MIN TEMP*). However, their estimated coefficients are both statistically insignificant.[20] In contrast, the second weather variable (*PRECIPITATION*) has a positive and significant coefficient, meaning that more intense precipitation in a Zone has a negative effect on service quality.

To account for potentially (unobserved) factors correlated with the changes in regulatory period, we interact all independent variables with a dummy (*REGII*) that takes value 1 for all observations in years 2008 and 2009. Results are reported in Column (4). We find that all technical interacted variables are insignificant, meaning that their effect on the dependent variable does not differ across the two regulatory periods. The only significant interaction is with operational expenses, which appears to have negatively affected service quality in 2008 and 2009, possibly due to a prevalence of preventive costs (Jamasb et al., 2012). However, the sum of the coefficients on linear and interacted operational expenditures terms remains positive, confirming our previous results.

Finally, to test the robustness of our fixed effect estimates, we account for the potential endogeneity in this dynamic relationship. We thus include the lagged *SAIDI* in the regression and, we use the Arellano and Bond (1991) and Arellano and Bover (1995) linear generalized method of moments (GMM) estimators to deal with the dynamic panel bias and the potential endogeneity of other regressors.[21] To check the validity of the instrument set, we then

[20] As a robustness check, we also estimated the above models normalizing the independent variables with respect to the power sold (MWh). Our results remain consistent with those in Table 4. For this reason, and to save space, we do not report them in the paper, but make them available upon request.

[21] We use the dynamic System-GMM model developed by Arellano and Bond (1991) and Blundell and Bond (1998). This model estimates a system of level and first-differenced equations and uses lags of first-differenced

calculate the two-step Sargan-Hansen statistic under the null hypothesis of joint validity of the instruments and report the resulting p-values in Table 4 – Columns (5) and (6).[22] However, the Hansen test does not provide information on the strength, or relevance, of the instruments. Since no well-established criteria is available for evaluating the joint relevance of the instrument set (as for the standard two-stage least squares instrumental variable method), we follow the two-step procedure recently introduced by Wintoki *et al*. (2012) and calculate the Cragg-Donald Wald statistics, designed to test weak identification of the instrument set.[23]

Results in Columns (5) and (6) show that most of the variables keep the expected sign confirming previous results. *UNDER* remains negative and significant, *PRECIPITATION* enters with a positive and significant coefficient and the positive coefficient on *OPEX_LVcons* is not far from significance (p value = 0.12). Moreover, the GMM results show that the number of Petersen coils (*PC_LVcons*) has the expected negative and significant impact on *SAIDI* while *AUTO_LVcons* loses significance. Interestingly, we now find that both the share of non-residential energy consumption (*PERC_NR*) and the minimum temperature variable (*MIN TEMP*) enter significantly and with the expected negative sign in Column (5).

From a research perspective, our results add to previous literature by providing evidence on the role of specific, structural interventions on quality levels.[24] While grounding of feeders is a well-known, quality-enhancing strategy, to the best of our knowledge, the impact of network automation and neutral grounding has never been studied before. We can use our GMM estimates to find some quantitative implications. For example, doubling the average number of Petersen coils per 10^4 consumers, from 0.55 to 1.1, would lead to a decrease in

variables as instruments for equations in levels and lags of variables in levels as instruments for equations in first-differences. For the estimation, we used the *xtabond2* Stata module created by Roodman (2006).

[22] The set of instruments includes lags of all the variables in the regression as well as a number of external variables that account for the unit-specific environment: the size of the service area in km^2 (*AREA*); the area covered by forests, in *ha* (*FOREST*), and a dummy variable denoting proximity to the sea (*COAST*).

[23] The procedure adapts the two-stage procedure to the GMM-System estimation method and relies on the critical values developed by Stock and Yogo (2005) for testing weak identification as used in the 2SLS framework. Following Wintoki *et al.* (2012), and adapting to the system structure of GMM-System, we perform the test on the *levels* of endogenous variables regressed on the instruments in *first-differences* and obtain the first Cragg-Donald (CD) Statistic. Then, we regress the *first-differences* of the endogenous variables on the instruments in *levels* and obtain the second CD statistic. We finally compare the CD statistics with critical values by Stock and Yogo (2005). In Table 6 – Panel A, the values of the CD test are well above the critical value of 10, which is the "rule of thumb" critical value suggested for assessing strength of the instruments. See also Fremeth and Shavers (2014) for a similar implementation of the test.

[24] Differences in quality performance across Italian distribution units are associated with network structure and type of consumers served (Cambini et al., 2014). Since the latter can hardly be modified, it is not surprising that quality improvements in Italy are mainly driven by structural interventions (e.g., grounding of feeders and network automation).

SAIDI of around 3 minutes. By increasing the percentage of underground lines by one percentage point, the number of minutes lost per customer would decrease in the range of 2 to 4 minutes, depending on the specification; evaluated at the sample mean, this implies that SAIDI would decrease on average from 56 to 54-52 minutes per customer. Interestingly, one may also note that an increase of 100 mm of *PRECIPITATION* (from 783 mm to 883 mm at the sample mean) would increase SAIDI by about 2 minutes. Finally, the results for non-capital resources highlight the corrective role of operational costs, while evidence provided by Ter-Martirosyan and Kwoka (2010) supports the (preventive) effect of maintenance expenditures.

We now proceed to examine the direction of causality between output-based incentives and firm decisions on investment and operational expenditures. We are not aware of any previous work that uses Granger causality tests to this purpose.

5.2 The relationship between capital and non-capital expenditures and incentives (step two)

To test the direction of the relationship between incentives and capital resources we perform a Granger test by estimating the following bivariate vector autoregressive VAR(2) model for incentives and investment rates:

$$IK_{it} = \alpha_{t-1} IK_{i,t-1} + \alpha_{t-2} IK_{i,t-2} + \beta_{t-1}^{INC} INC_{i,t-1} + \beta_{t-2}^{INC} INC_{i,t-2} + \mu_i + \lambda_t + \varepsilon_{it}^{IK} \qquad (3)$$

$$INC_{it} = \alpha_{t-1}^{IK} IK_{i,t-1} + \alpha_{t-2}^{IK} IK_{i,t-2} + \beta_{t-1} INC_{i,t-1} + \beta_{t-2} INC_{i,t-2} + \mu_i + \lambda_t + \varepsilon_{it}^{INC} \qquad (4)$$

where IK_{it} is the ratio between gross fixed investment and the beginning of the year capital stock at replacement value, INC_{it} is the inflation corrected amount of incentives, μ_i and λ_t are the Zone and year dummies, and ε_{it}^{IK} and ε_{it}^{INC} are the error terms.

Following the reasoning in Section 3, the hypothesis that, conditional on individual and time effects, incentives Granger-cause firm investments, but not vice versa, requires that β_{t-1}^{INC} and β_{t-2}^{INC} are positive and jointly significant in equation (3), while α_{t-1}^{IK} and α_{t-2}^{IK} are not significant in equation (4). In other words, it requires that past incentives ($INC_{i,t-1}$ and $INC_{i,t-2}$) contribute significantly to the investment rate in regression (3), while past investments ($IK_{i,t-1}$ and $IK_{i,t-2}$) do not contribute significantly to determine incentives in equation (4).

In order to control that the total effect of the incentives on investment is positive as well as significant, we test the joint significance of the once and twice-lagged coefficients as well as their sum and report the p-values of the Wald tests with the regression results in Table 5 – Panel A.

A main concern when estimating a dynamic model as in equations (3) and (4) is that the lagged dependent variables are endogenous to the fixed effects in the error term, thus giving rise to a dynamic panel bias. As before, we rely on the GMM estimators and we calculate the two-step Sargan-Hansen statistic under the null hypothesis of joint validity of the instruments and report the resulting p-values in Table 5 – Panel A.[25] To ensure that the lagged variables are valid instruments, we also present the AR(1) autocorrelation test for the first-differenced error terms.[26]

The results from estimating equations (3) and (4) are in the first two columns. The results in Column (1) show that only the twice-lagged incentive term is statistically significant. However, the Wald test indicates that the first and second lags of the incentives in Column (1) are jointly significant in explaining the investment rate. Moreover, quite importantly, the sum of their coefficients is positive and significant. In contrast, in Column (2), the lagged investment terms are insignificant and do not contribute, either individually or jointly, to explain the amount of incentives granted to the distribution Zone. The results of the test indicate that lagged incentives contribute significantly to determine the investment rate of a Zone, and not vice-versa. From a research perspective, our results add to the existing literature by establishing a direction in the causality between incentives provided by the regulatory authority (in previous periods) and the firm's investment decision.

We then turn to the relationship between incentives and operational expenses by using the following bivariate Granger causality test:

$$OpK_{i,t} = \alpha_{t-1} OpK_{i,t-1} + \alpha_{t-2} OpK_{i,t-2} + \beta_{t-1}^{INC} INC_{i,t-1} + \beta_{t-2}^{INC} INC_{i,t-2} + \mu_i + \lambda_t + \varepsilon_{it}^{OpK} \quad (5)$$

[25] The Sargan-Hansen test is robust, but may be weakened if there are too many instruments with respect to the number of observations (Roodman, 2006). Therefore we follow a conservative strategy using no more than one/two lags of the instrumenting variables (i.e. the third or fourth lags in our case), to assure that the number of instruments is not greater than the number of firms. The rather demanding time structure of the Granger test and of the GMM-System estimator is also the reason why the number of observations drops from 690 in Table 4 to 345 in Table 5 – Panel A (although of course all observations are used in the estimation).

[26] The AR(2) tests of the second-order correlation in the first-differenced residuals could not be calculated by STATA due to length of our time series. However, the purpose of the AR(2) test is to assess the validity of instruments lagged two years and in case of invalidity of the instrument, the third lag has to be used. As explained in the footnote above, the third lag of the variable is indeed the earliest instrument that we use, hence the AR(2) test is not relevant to us.

$$INC_{i,t} = \alpha_{t-1}^{OpK} OpK_{i,t-1} + \alpha_{t-2}^{OpK} OpK_{i,t-2} + \beta_{t-1} INC_{i,t-1} + \beta_{t-2} INC_{i,t-2} + \mu_i + \lambda_t + \varepsilon_{it}^{INC} \quad (6)$$

where $OpK_{i,t}$ is the ratio between the operational expenses in year *t* and the capital stock in year *t-1*. As before, our hypothesis requires that both β_{t-1}^{INC} and β_{t-2}^{INC} are positive and jointly significant in equation (5), while α_{t-1}^{OpK} and α_{t-2}^{OpK} are not significant in equation (6).

Results in Columns (3) and (4) of Table 5 – Panel A show that lagged incentives contribute significantly to explaining the variable *OpK*, but the two coefficients β_{t-1}^{INC} and β_{t-2}^{INC} bear opposite signs. While incentives granted one-year ago appear to increase operational expenses, incentives granted two years ago appear to reduce them. Not surprisingly, the sum of the two coefficients is not significantly different from zero, as shown by the test reported at the bottom of the column. When we test the reverse relationship, i.e. whether past operational expenses significantly determine incentives, we find that the coefficients on lagged operational expenses are never significant in the regression where the dependent variable is the amount of incentives to the Zone.

Overall, the results in Columns (3) and (4) do not support any direction in the causality between incentives and operational expenses, possibly due to our inability to separate preventive from corrective costs in the data.[27]

To further test the robustness of our analysis, we also run the Granger tests replacing *INC* (incentives) with *REWARDS* (i.e. positive incentive payments) as the main variable of interest. Results are reported in Table 5 – Panel B. The results show that (past) rewards do affect investment rate, but not vice versa. Once again, the evidence when we use operational expenses does not allow us to establish the direction of the causality between rewards and operational expenditures. Overall, this further evidence is consistent with the results in Table 5-Panel A.

5.3 The impact of quality-related incentives and the asymmetric effect of penalties and rewards (step three)

In this section, we expand the scope of the analysis of the relationship between investment and incentives by testing if past incentives still affect investment after controlling

[27] We recall that previous literature has found (weak) evidence that quality standards (not necessarily output-based incentives) result in greater maintenance expenditures (Ter-Martisoryan and Kwoka, 2010). We must postpone further investigation until this distinction in the data becomes available.

for other potential determinants and whether penalties and rewards have similar or asymmetric effects on investment.

We conjecture that rewards and penalties received act as a signal (more or less effective) of the adequacy of the expenditure decisions made by the firm to control continuity of supply: a reward indicates that firm decisions were more than adequate (above the regulatory expectations) and vice versa. Hence, we expect penalties to stimulate investments: even if the firm (on a rational basis) had not spent on quality in the previous period, it should be more prone to invest after receiving a penalty. As for rewards, we have equal expectations for both types of responses. On the one hand, a premium might reinforce the firm's willingness to take additional measures to reduce outages. On the other hand, it may also induce the firm simply to provide an adequate level of performance.

For a basic empirical model, we rely on the micro econometric literature on company investment, which suggests to include the *lagged investment ratio* (I_{t-1}/K_{t-2}) to account for capital stock adjustment; *demand growth*, as measured by the change in sales[28] to capital stock ratio [$\Delta(S_t/K_{t-1})$], to account for accelerator effects and for future investment opportunities; and the operating cash flow to capital stock ratio (Π_t/K_{t-1}) to control for *financing constraints* due to imperfect capital markets and asymmetric information.[29]

We augment this model by adding the monetary incentives, normalized with respect to beginning of the year capital stock (at replacement value, as usual). We start with the aggregate incentive variable (INC_t/K_{t-1}), which can take positive or negative values, then we test the effect of rewards ($REWARD_t/K_{t-1}$) and finally we turn to penalties ($PENALTY_t/K_{t-1}$), all of which entered separately in the investment specification. The baseline specification is the following:

$$IK_{i,t} = \alpha_0 + \alpha_1 IK_{i,t-1} + \alpha_2 \Delta SK_{i,t} + \alpha_3 \Pi K_{i,t} + \alpha_4 INCK_{i,t-1} + \lambda_t + \mu_i + \varepsilon_{it} \qquad (7)$$

where $INCK_{i,t-1}$ is alternatively replaced by $REWARDK_{i,t-1}$, $PENALTYK_{i,t-1}$; λ_t and μ_i are the Zone and year dummies, while ε_{it} is the error term.

To estimate the dynamic investment model in equation (7) with panel data, we rely on the linear generalized method of moments (GMM) estimator (see Section 5.2 and footnotes 20

[28] Recall that revenues from tariffs (i.e. sales) also cover quality-related costs for the provision of target SAIDI.
[29] See, for example, Hubbard (1998) for a comprehensive survey of company investment models estimated with panel data, Fazzari et al. (1988) for a seminal contribution, Lyon and Mayo (2005) for an application to the US electric utility industry and Cambini and Rondi (2010) for an application to EU energy companies.

and 21).[30] Similarly to the results for the Granger tests, we report the two-step Sargan-Hansen statistic under the null hypothesis of joint validity of the instruments, the difference in Hansen test of exogeneity (which compares full and restricted models to assess the orthogonality of the instruments) and the AR(1) and AR(2) autocorrelation tests for the first-differenced error terms. Moreover, as in Section 5.1, we also calculate the Cragg-Donald Wald statistics, designed to test weak identification of the instrument set.

We report the results in Table 6 – Panel A, where in Column (1) we examine the effect of the aggregate incentive variable and in Columns (2) and (3) we test the separate effect of rewards and penalties.[31]

In all Columns, both demand growth and the cash-flow to capital ratio enter with a positive and significant coefficient, suggesting that demand and financial factors do matter for the investment decisions. Moreover, the lagged investment term is positive and not too far from significance in most specifications. Having established that the usual control variables work as expected, we turn to the effect of the output-based incentive scheme, which is the focus of the paper.

We start by testing, in Column (1), the effect of the aggregate measure of monetary incentives (INC_t/K_{t-1}). The estimated coefficient is positive, but insignificant, possibly because the effects of rewards and penalties cancel each other out in this specification, i.e. after controlling for other determinants of investment.

To pin down the effect of the output-based incentives policy we thus follow an alternative route and test, separately, the role of reward and penalties. If both types of incentives are "successful" in fostering capital expenditures, we should find that *REWARDK* carries a positive sign, while *PENALTYK* should enter with a negative coefficient. This is what we find when we look at Columns (2) and (3) in Table 6 – Panel A. However, while the negative coefficient on *PENALTYK* is statistically significant (with a p-value of 0.022), the coefficient on *REWARDK* is positive but insignificant. This indicates that the firm responds more reactively to negative, than to positive incentives.

These findings reveal an asymmetric effect of rewards and penalties, where rewards that do not seem to significantly affect the firm's investment decision while penalties apparently

[30] The set of instruments includes lags of investment, sales, cash flow and incentives (or rewards or penalties) to capital stock ratios as well as a number of external variables that account for the unit-specific environment: the percentage of the non residential energy consumption (*PERC_NR*); zonal density, measured by the number of LV consumers over network length (*DENSITY*); the area covered by forests, in *ha* (*FOREST*), and a dummy variable indicating Zones in the North of the country (*NORTH).*

[31] We also checked the fixed effect results from the static version of the investment model and we found that they hold. Results are available on requests.

do. To throw some light on this result, in Table 6 – Panel B we divide the sample in subgroups according to different levels of quality performance, i.e. by SAIDI quartiles, and then test whether rewards and penalties present a differentiated impact in Zones with different quality performance.[32] In Column (1), we analyze the effect of regulatory incentives on highly performing units in terms of quality, i.e. in Zones with the SAIDI indicator below 32 minutes (top quartile). Results show that rewards do matter in top quality performance Zones, and that they positively affect the investment rate. When we turn to Zones in the range of intermediate quality performance (second and third quartiles) we find that neither rewards (Column 2) nor penalties (Column 3) display a significant effect on investment. Finally, when we look at the sub-sample of units with the lowest quality of service (above 73.9 minutes), we find that the coefficient on *PENALTYK* is negative and significant, which, recalling that the variable is entered with a negative sign, means that penalties have a positive effect on the investment rate. If we translate the estimated coefficients into quantitative effects, we find that a 1 percentage point increase in the reward to capital stock ratio for high performing units would lead to a 0.4% increase in the investment rate; evaluated at the sample mean, this implies an increase from 6.6% to 7%. Turning to penalties, and taking into account that they are on average quite lower than rewards (see Tables 2 and 3), we find that by doubling the mean *PENALTYK* to less performing units from 0.35% to 0.70%, the investment rate would increase by 0.5 percentage points; that is, evaluated at the mean, from 5.8% to 6.2% (not far from the investment rate of the best performing units).

Not only this is a novel result from a research perspective, but it also conveys interesting policy insights into output-based regulation.[33] We find that the Italian incumbent distributor does respond to the signal provided by penalties received the year before by deploying capital resources to improve service quality. In other words, penalties paid in the past are effective in inducing the firm to exert effort aimed at improving quality, and especially so if it operates in area with a low quality performance. As for rewards, we interpret the lack of statistical significance in the majority of areas as an indication that ENEL Distribuzione views positive monetary incentives as a signal that their level of output is adequate.

[32] We thank an anonymous referee for suggesting us this further analysis.

[33] Using a different empirical approach, Poudineh and Jamasb (2015) find that the cost of energy-not-supplied seems relevant in explaining the investment behavior of Norwegian electricity distribution companies. However, their results suggests that investments have mainly been of a corrective nature rather than a preventive one (they are a response to outages in the same time period).

Accordingly, rewards granted the year before are less likely to lead the firm to invest further (i.e. to exercise an additional effort).

6. Conclusions and policy implications

Using detailed micro data for the largest Italian electricity distributor, this paper sheds some light on the relation between quality-based incentives and the incumbent's decisions about capital and operational expenditures that enable it to meet a given regulatory target. Studying if and how this type of incentives are effective in inducing firms to meet a given regulatory target is crucial, not only because of the practical complexity implied by these regulatory mechanisms, but also because regulatory agencies appear to be expanding the set of outputs that are subject to rewards and penalties schemes.

To this end, we make use of data on service quality in electricity distribution, which we consider as an example of a desirable output that regulators may want firms to pursue. We begin by providing evidence that investments in specific physical assets are effective in enhancing the level of service quality. This adds to previous literature that focused on the effect of operational expenditures. Then, we concentrate on the direction of causality between quality incentives and the use of firms' capital and non-capital resources. We determine that incentives Granger-cause capital expenditures (and not vice-versa). Hence, we proceed to verify whether incentives continue to affect firms' decision to invest, after we account for other potential determinants of the investment rate. Our results show that (paid) output-based penalties are more effective than rewards in prompting the incumbent to invest capital resources to improve their performance. When we decouple penalties and rewards, we find that penalties have a significant and positive effect on the investment rate, and especially so in areas with low quality performance but not within distribution units with intermediate quality. As for rewards, we find that they positively and significantly affect investment decisions only within areas with top quality performance. In contrast, we find that the impact of rewards is insignificant within distribution units with intermediate quality, which suggests that the incumbent probably interprets rewards as a premium for achieving a desirable level of performance, but not as a stimulus to exert an additional effort. The lack of statistical significance of both rewards and penalties in these latter areas suggests that monetary incentives does not provide any relevant signal to the regulated firm. Overall, the evidence of an asymmetric role of quality-related incentives suggests that penalties and rewards should separately analyzed when assessing the effectiveness of an output-based regulatory policy.

These results question the usefulness of maintaining a two-side (positive and negative) incentive scheme over the entire range of output levels, as well as the use of both types of incentives over a relatively wide output range, where they seem to be not effective (or no longer effective). These considerations appear relevant in light of the complex implementation of these incentive schemes and the associated costs incurred in practice by the regulatory authority.

On the policy ground, our results also suggest that in practice, regulators might consider whether assign incentives only for extremely high or low levels of performance or, considering the timing of the investment process, perhaps assign them less frequently, i.e. not every year, but eventually only once in every regulatory period. This would have the advantage of preserving the incentive mechanism while assigning a lower number of rewards/penalties and incurring in lower regulatory costs.

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Table 1. Variables' descriptions

Variable name	Label	Description
SAIDI	System Average Interruption Duration Index	Average duration of long, unplanned interruptions per customer (in minutes).
INC	Regulatory incentives	Amounts received in rewards or paid in penalties (the variable assume either a positive or a negative sign). In constant euros (base 2005).
REWARD	Rewards	Equal to the variable *INC* if this is positive (and zero otherwise). In constant euros (base 2005).
PENALTY	Penalties	Equal to the variable *INC* if this is negative (and zero otherwise). In constant euros (base 2005).
UNDER	Percentage of underground cable	Ratio of underground cable length over total network length.
AUTO_LVcons	Number of automated secondary substations per Low Voltage (LV) consumer	Ratio of the number of automated secondary substations over the number of LV consumers.
PC_LVcons	Number of Petersen coils per LV consumer	Ratio of the number of Petersen coils over the number of LV consumers.
PERC_NR	Percentage of non-residential energy consumption	Ratio of LV non-residential energy consumption plus Medium Voltage (MV) energy consumption to total energy consumption.
OPEX	Operational expenditures	Sum of costs incurred for labor, services, materials and other costs. In constant euros (base 2005).
OPEX_LVcons	Operational expenditures per LV consumer	Ratio of operational expenditures to the number of LV consumers. In constant euros (base 2005).
PRECIPITATION	Precipitation	Yearly average amount of rain, snow, sleet, or hail that falls to the ground (in mm)
MIN TEMP	Minimum temperature	Yearly average minimum temperature (in Celsius degrees)
IK	Investment rate	Ratio of investments (*I* in *t*) to the beginning of year capital stock, at replacement value (*K* in *t*-1).
ΠK	Operating cash flow to capital stock ratio	Ratio of operating cash flow (*Π* in *t*) to the beginning of year capital stock, at replacement value (*K* in *t*-1).
SK	Sales to capital stock ratio	Ratio of sales (*S* in *t*) to the beginning of year capital stock, at replacement value (*K* in *t*-1).
OpK	Operational expenditures to capital stock ratio	Ratio of operational expenditures (*OPEX* in t) to the beginning of year capital stock, at replacement value (*K* in *t*-1).
INCK	Incentives to capital stock ratio	Ratio of incentives (*INC* – not adjusted for inflation – in year *t)* to the beginning of year capital stock, at replacement value (*K* in year *t*-1).
REWARDK	Rewards to capital stock ratio	Ratio of rewards (*REWARD* – not adjusted for inflation – in year *t*) in year *t* t to the beginning of year capital stock, at replacement value (*K* in year *t-1*).
PENALTYK	Penalties to capital stock ratio	Ratio of penalties (*PENALTY* – not adjusted for inflation – in year *t*) to the beginning of year capital stock, at replacement value (*K* in year *t-1*).
COAST	Proximity to the sea	Dummy variable that takes the value 1 when a Zone is close to the sea
NORTH	North of Italy	Dummy variable that takes the value 1 when a Zone is located in the North of the country
AREA	Dimension of the service area	Total area covered (in km^2)
DENSITY	Consumer density	Ratio of number of LV consumer to network length
FOREST	Area covered by forest	Hectares of land covered by forest

Table 2 – Summary statistics

Variable	Mean	Std. Dev.	Min	Max	N. Obs.
SAIDI (minutes)	56.34	31.56	10.42	194.28	690
INC (M€)	0.87	1.13	-3.07	8.77	690
REWARD (M€)	0.90	1.09	0.00	8.77	690
PENALTY (M€)	0.03	0.18	0.00	3.07	690
UNDER (%)	0.71	0.12	0.46	0.97	690
AUTO_LVcons (n./10^2 consumers)	2.80	0.076	0.123	0.849	690
PC_LVcons (n./10^4 consumers)	0.549	0.379	0.00	2.34	690
PERC_NR (%)	0.72	0.08	0.51	0.85	690
OPEX (M€)	17.19	8.52	4.13	50.48	690
OPEX_LVcons (€/consumer)	65.04	10.87	43.20	112.52	690
PRECIPITATION (mm)	782.90	173.51	406	1378.7	690
MIN TEMP (°C)	8.81	2.86	-1.5	15.2	690
IK	0.06	0.02	0.00	0.26	575
ΠK	0.24	0.10	0.07	0.96	575
SK	0.34	0.11	0.14	1.15	575
OpK	0.14	0.03	0.06	0.40	690
INCK	0.009	0.010	-0.012	0.087	575
REWARDK	0.009	0.010	0.00	0.087	575
PENALITYK	0.0003	0.0013	0.00	0.012	575
AREA (km^2)	2480.22	1445.81	130.92	7274.35	690
COAST	0.54	0.50	0	1	690
NORTH	0.42	0.49	0	1	690
DENSITY (consumers/km)	28.71	11.68	13.07	82.94	690
FOREST (ha)	106,310	98,638	2,519	422,772	690

Table 3 – Average level of the main economic variables by service quality defined as SAIDI quartiles

Service Quality (SAIDI, minutes)	*Investment/ Capital Stock (IK)*	*Operation Exp./ Cap. Stock (OpK)*	*Incentives/ Cap. Stock (INCK)*	*Incentives/ Op.Ex/ (%)*	*Rewards/ Investment (%)*	*Penalties/ Investment (%)*
SAIDI < 32	0.066	0.149	0.015	10.1	22.8	0.002
32 ≤ *SAIDI* < 47.7	0.062	0.140	0.010	7.1	18.3	0.074
47.7 ≤ *SAIDI* < 73.9	0.058	0.143	0.005	3.5	12.8	0.79
SAIDI ≥ 73.9	0.058	0.138	0.003	2.2	9.5	1.92

Table 4. Technical and economic determinants of continuity of supply (SAIDI)

Dep. Variable: *SAIDI*	(1) Physical Equipment	(2) Operational expenditures	(3) Physical Equipment and Operational expenditures	(4) Controlling for regulatory periods	(5) Physical Equipment	(6) Physical Equipment and Operational expenditures
	Fixed Effects				**GMM**	
UNDER	-426.91**	-	-334.46*	-268.24	-469.00***	-260.52**
	(211.86)	-	(195.97)	(235.99)	(125.75)	(132.81)
AUTO_LVcons	-51.83**	-	-52.91**	-57.54**	-10.82	-36.56
	(4.21)	-	(22.07)	(26.47)	(19.19)	(26.02)
PC_LVcons	-3.584	-	-1.854	-1.223	-6.274*	-6.687**
	(4.21)	-	(4.078)	(3.913)	(3.464)	(3.363)
OPEX_LVcons	-	1.162***	1.056***	1.041***	-	0.451
	-	(0.324)	(0.309)	(0.314)	-	(0.290)
PERC_NR	118.62	144.08	146.02	186.11	-129.31***	-109.93***
	(131.41)	(125.39)	(126.12)	(137.43)	(22.74)	(22.74)
PRECIPITATION	0.025***	0.025***	0.023***	0.023***	0.020***	0.019***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)
MIN TEMP	2.486	1.775	1.635	2.001	-1.235**	-0.824
	(2.16)	(1.960)	(2.026)	(2.069)	(0.62)	(0.532)
$SAIDI_{t-1}$	-	-	-	-	0.453***	0.478***
	-	-	-	-	(0.065)	(0.059)
UNDER*REGII	-	-	-	-0.98	-	-
	-	-	-	(17.00)	-	-
AUTO_LVcons*REGII	-	-	-	15.00	-	-
	-	-	-	(21.72)	-	-
PC_LVcons*REGII	-	-	-	-1.982	-	-
	-	-	-	(3.870)	-	-

OPEX_LVcons*REGII	-	-	-	-0.583**	-	-
	-	-	-	(0.265)	-	-
Constant	256.62	-156.74	99.32	23.79	152.78***	98.64***
	(182.04)	(94.12)	(183.55)	(219.50)	(25.61)	(35.52)
Unit dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.358	0.368	0.383	0.392	-	-
AR(1)	-	-	-	-	0.000	0.000
AR(2)	-	-	-	-	0.332	0.418
Sargan-Hansen Test (p value)	-	-	-	-	0.202	0.171
Cragg-Donald weak identification test statistic (levels)	-	-	-	-	11.3	7.31
Cragg-Donald weak identification test statistic (first-diff)	-	-	-	-	33.29	26.47
Observations	690	690	690	690	575	575
Number of units	115	115	115	115	115	115

All variables are defined in Table 1. Robust standard errors in parentheses:
*** p<0.01, ** p<0.05, * p<0.1

Table 5 – Panel A. Granger Tests: relationship between investment and incentives and between operational expenditures and incentives

Investment and Incentives				*Operational expenditures and Incentives*			
Dep. Variable: *IK*		Dep. Variable: *INC*		Dep. Variable: *OpK*		Dep. Variable: *INC*	
α_{t-1}	-0.324	α_{t-1}^{IK}	-38.178	α_{t-1}	0.819***	α_{t-1}^{OpK}	13.768
	(0.418)		(37.644)		(0.301)		(13.318)
α_{t-2}	-0.160*	α_{t-2}^{IK}	-8.880	α_{t-2}	0.121***	α_{t-2}^{OpK}	5.230
	(0.086)		(8.290)		(0.035)		(5.843)
β_{t-1}^{INC}	-0.001	β_{t-1}	0.202	β_{t-1}^{INC}	0.002*	β_{t-1}	0.259**
	(0.002)		(0.135)		(0.001)		(0.107)
β_{t-2}^{INC}	0.005**	β_{t-2}	0.348	β_{t-2}^{INC}	-0.003***	β_{t-2}	0.105
	(0.002)		(0.221)		(0.001)		(0.071)
Constant	0.082**	Constant	3.099	Constant	0.025	Constant	-2.465
	(0.035)		(3.021)		(0.043)		(2.378)
P-value test on H0: $\beta_{t-1}^{INC} = \beta_{t-2}^{INC} = 0$	0.038	P-value test on H0: $\alpha_{t-1}^{IK} = \alpha_{t-2}^{IK} = 0$	0.558	P-value test on H0 $\beta_{t-1}^{INC} = \beta_{t-2}^{INC} = 0$	0.007	P-value test on H0: $\alpha_{t-1}^{OpK} = \alpha_{t-2}^{OpK} = 0$	0.582
P-value test on H0: $\beta_{t-1}^{INC} + \beta_{t-2}^{INC} = 0$	0.079	P-value test on H0: $\alpha_{t-1}^{IK} + \alpha_{t-2}^{IK} = 0$	0.299	P-value test on H0: $\beta_{t-1}^{INC} + \beta_{t-2}^{INC} = 0$	0.597	P-value test on H0: $\alpha_{t-1}^{OpK} + \alpha_{t-2}^{OpK} = 0$	0.301
Obs. [Nr. Unit]	345 [115]	Obs. [Nr. Unit]	345 [115]	Obs. [Nr. Unit]	345 [115]	Obs. [Nr. Unit]	345 [115]
Hansen test	0.648	Hansen test	0.293	Hansen test	0.513	Hansen test	0.027
AR1	0.910	AR1	0.218	AR1	0.100	AR1	0.014

All variables are defined in Table 1. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10

Table 5 – Panel B. Granger Tests: relationship between investment and rewards and between operational expenditures and rewards

Investment and Rewards				*Operational expenditures and Rewards*			
Dep. Variable: *IK*		Dep. Variable: *REWARD*		Dep. Variable: *OpK*		Dep. Variable: *REWARD*	
α_{t-1}	-0.204	α_{t-1}^{IK}	-27.167	α_{t-1}	0.655*	α_{t-1}^{OpK}	30.819
	(0.407)		(33.877)		(0.379)		(26.279)
α_{t-2}	-0.187*	α_{t-2}^{IK}	-8.177	α_{t-2}	0.089***	α_{t-2}^{OpK}	6.705
	(0.112)		(9.495)		(0.028)		(8.150)
β_{t-1}^{INC}	-0.002	β_{t-1}	0.294**	β_{t-1}^{INC}	0.002	β_{t-1}	0.331**
	(0.003)		(0.128)		(0.002)		(0.146)
β_{t-2}^{INC}	0.007**	β_{t-2}	0.311	β_{t-2}^{INC}	-0.002**	β_{t-2}	0.012
	(0.003)		(0.237)		(0.001)		(0.088)
Constant	0.067**	Constant	2.240	Constant	0.047	Constant	-4.601
	(0.033)		(2.699)		(0.049)		(4.350)
P-value test on H$_0$: $\beta_{t-1}^{INC}=\beta_{t-2}^{INC}=0$	0.020	P-value test on H$_0$: $\alpha_{t-1}^{IK}=\alpha_{t-2}^{IK}=0$	0.668	P-value test on H$_0$ $\beta_{t-1}^{INC}=\beta_{t-2}^{INC}=0$	0.096	P-value test on H$_0$: $\alpha_{t-1}^{OpK}=\alpha_{t-2}^{OpK}=0$	0.448
P-value test on H$_0$: $\beta_{t-1}^{INC}+\beta_{t-2}^{INC}=0$	0.027	P-value test on H$_0$: $\alpha_{t-1}^{IK}+\alpha_{t-2}^{IK}=0$	0.407	P-value test on H$_0$: $\beta_{t-1}^{INC}+\beta_{t-2}^{INC}=0$	0.881	P-value test on H$_0$: $\alpha_{t-1}^{OpK}+\alpha_{t-2}^{OpK}=0$	0.268
Obs. [Nr. Unit]	286 [112]	Obs. [Nr. Unit]	286 [112]	Obs. [Nr. Unit]	286 [112]	Obs. [Nr. Unit]	286 [112]
Hansen test	0.643	Hansen test	0.158	Hansen test	0.496	Hansen test	0.125
AR1	0.720	AR1	0.122	AR1	0.144	AR1	0.033

All variables are defined in Table 1. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10

Table 6 – Panel A: Investment analysis - GMM estimations

Dep. Variable: $IK_{i,t}$	(1) *Incentives*	(2) *Rewards*	(3) *Penalties*
$IK_{i,t\text{-}1}$	0.107	0.105	0.118
	(0.089)	(0.089)	(0.085)
$\Delta SK_{i,t}$	0.133***	0.133***	0.134***
	(0.024)	(0.024)	(0.022)
$\Pi K_{i,t}$	0.066***	0.068***	0.081***
	(0.018)	(0.019)	(0.015)
$INCK_{i,t\text{-}1}$	0.241	-	-
	(0.196)	-	-
$REWARDK_{i,t\text{-}1}$	-	0.233	-
	-	(0.207)	-
$PENALTYK_{i,t\text{-}1}$	-	-	-1.552**
	-	-	(0.679)
Constant	0.033***	0.033***	0.030***
	(0.006)	(0.006)	(0.006)
Unit dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
AR1 *(p-value)*	0.006	0.006	0.005
AR2 *(p-value)*	0.556	0.559	0.735
Hansen test of over-identification *(p-value)*	0.454	0.477	0.673
Diff-in-Hansen test of exogeneity (*p-value*)	0.900	0.802	0.922
Number of Instruments	25	25	27
Cragg-Donald weak identification test statistic (levels)	31.49	31.19	40.88
Cragg-Donald weak identification test statistic (first-diff)	67.50	61.36	75.89
Observations	460	460	460
Number of units	115	115	115

All variables are defined in Table 1. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10

Table 6 – Panel B: Investment analysis - GMM estimations with Subsamples

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10

Dep. Variable: $IK_{i,t}$	**(1)** *High performance units* (SAIDI ≤ 32) **I Quartile**	**(2)** *Average performance Units* (32 < SAIDI < 73.9) **II-III Quartile**	**(3)** *Average performance Units* (32 < SAIDI < 73.9) **II-III Quartile**	**(4)** *Low performance Units* (SAIDI ≥ 73.9) **IV Quartile**
$IK_{i,t-1}$	0.099	0.173	0.112	0.342
	(0.072)	(0.199)	(0.152)	(0.276)
$\Delta SK_{i,t}$	0.160***	0.169***	0.168**	0.585**
	(0.021)	(0.066)	(0.085)	(0.245)
$\Pi K_{i,t}$	0.074**	0.186**	0.189***	0.074
	(0.030)	(0.080)	(0.071)	(0.077)
$REWARDK_{i,t-1}$	0.417**	-0.226	-	-
	(0.212)	(0.185)	-	-
$PENALTYK_{i,t-1}$	-	-	-0.704	-1.459*
	-	-	(1.015)	(0.767)
Constant	0.030***	0.003	0.006	0.017
	(0.008)	(0.016)	(0.017)	(0.026)
Unit dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
AR1 *(p-value)*	0.009	0.054	0.047	0.053
AR2 *(p-value)*	0.744	0.907	0.832	0.780
Hansen test *(p-value)*	0.155	0.365	0.414	0.107
Diff-in-Hansen test of exogeneity (*p-value*)	0.100	0.115	0.226	0.355
Number of Instruments	25	21	21	21
Observations	138	238	236	86
Number of units	44	83	83	36

All variables are defined in Table 1. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10